International Journal of Health Sciences
Available online at www.sciencescholar.us
E-ISSN: 2550-696X
Int. J. of Health Sci.
DOI: 10.53730

How to Cite:
Djamba, K. J., Havyarimana, V., Mbabazi, P. B., & Niyongabo, J. (2026). A context-aware adoption model for e-health systems in fragile health sectors: The case of the Democratic Republic of Congo. *International Journal of Health Sciences*, *10*(S1), 125–160.
https://doi.org/10.53730/ijhs.v10nS1.15927

A context-aware adoption model for e-health systems in fragile health sectors: The case of the Democratic Republic of Congo

Kalema Josue Djamba
Ph.D., Candidate at Doctoral School, University of Burundi, Bujumbura, Burundi

Vincent Havyarimana
Full Professor, Department of Computer Engineering, Ecole Normale Superieur, Bujumbura

Phelix Businge Mbabazi
Professor, Department of Information Systems, University of Kabale, Kabale, Uganda

Julius Niyongabo
Ph.D., Department of Information Systems, University of Burundi, Bujumbura, Burundi

***Abstract*---**The adoption of e-health systems has become a key driver of healthcare modernization and service delivery improvement worldwide. However, the implementation of digital health technologies remains particularly challenging in fragile healthcare systems characterized by limited infrastructure, institutional constraints, and resource shortages. This study develops and validates a context-aware adoption model for e-health systems in the healthcare sector of the Democratic Republic of Congo (DRC).Building upon established technology adoption theories, specifically the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), this research integrates additional contextual factors relevant to fragile healthcare environments, including ICT infrastructure, trust, privacy

***Corresponding author**: Djamba, K.J.; Email: josuekalema@gmail.com*
Submitted: 27 Jan 2026, Revised: 09 March 2026, Accepted: 18 April 2026

and security, and the policy and regulatory environment. Data were collected from healthcare professionals and analyzed using statistical methods to evaluate the relationships between technological, organizational, social, and institutional determinants influencing behavioral intention and actual use of e-health systems.The results indicate that perceived usefulness and perceived ease of use significantly influence healthcare professionals' behavioral intention to adopt e-health technologies. Social influence and institutional support also play a meaningful role in shaping adoption behavior. Furthermore, facilitating conditions and ICT infrastructure significantly affect the actual use of e-health systems, while trust, privacy, and security concerns remain essential determinants in fragile health systems.The study contributes to the digital health literature by proposing and empirically validating a context-aware e-health adoption model adapted to resource-constrained healthcare environments. The findings provide practical insights for policymakers, healthcare institutions, and system designers aiming to implement sustainable and effective e-health solutions in the Democratic Republic of Congo and similar developing countries.

***Keywords*---**E-Health Adoption, Digital Health, Technology Acceptance Model, UTAUT, Health Information Systems, Developing Countries, Democratic Republic of Congo.

Introduction

The digital transformation of healthcare systems through information and communication technology (ICT) is now a strategic priority for improving the quality, accessibility, and efficacy of care on a global level. Digital health systems, including electronic health records, telemedicine platforms, health information exchanges, and mobile health applications, have the potential to improve clinical decision-making, facilitate patient management, and support evidence-based care (Ráti & Ildikó, 2023). In developed countries as well as developing countries, the role of digital health technology for strengthening health systems and achieving universal health coverage is growing (Vest, 2010) (Barlow, Bayer, & Curry, 2006). Despite these encouraging advantages, e-health system acceptance and implementation are still inconsistent throughout the world (Walle, et al., 2023). While many industrialized nations have effectively incorporated digital health technologies into their healthcare systems, developing nations especially those with weak health systems continue to confront formidable obstacles. These issues include a lack of ICT infrastructure, inadequate institutional support, healthcare workers' lack of digital skills, lax regulatory frameworks, and worries about data security and privacy. Therefore, a deeper understanding of the technological and contextual factors influencing user acceptance and system utilization is necessary for the successful implementation of e-health solutions in such situations (Djamba, et al 2025). An especially pertinent setting for examining these problems is the Democratic Republic of the Congo (DRC). The Democratic Republic of the Congo, one of the biggest nations in Sub-Saharan Africa, has a number of structural issues with its healthcare system, such as

inadequate infrastructure, a lack of skilled medical professionals, and disjointed health information management systems (Djamba, et al., 2025) (WHO., 2023) (Kalema , 2022).The promotion of digital health technologies as a way to improve healthcare service delivery has been the focus of national and international initiatives in recent years. However, a number of institutional, organizational, and technological obstacles continue to impede the uptake and efficient use of e-health systems (Djamba, Havyarimana, Mbabazi, & Niyongabo, 2025).For e-health efforts to be implemented successfully throughout the nation, it is therefore essential to comprehend the elements that affect healthcare professionals' acceptance and usage of digital health technologies (Djamba, Havyarimana, Mbambazi, & Niyongabo, 2025). To explain technology adoption behavior, a number of theoretical frameworks have been established within the subject of information systems research (F. Davis, 1989). The Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM) are two of the most popular models (Ursavaş, 2022). These models have been widely used in a variety of fields, including healthcare, to investigate user adoption of information systems. They emphasize the significance of important factors that shape people's behavioral intention to adopt new technologies, including perceived utility, perceived ease of use, social influence, and facilitating situations. However, current adoption models frequently pay little consideration to broader contextual conditions, especially in delicate healthcare situations, and instead concentrate exclusively on individual views and organizational aspects (Alsswey & Al-Samarraie, 2019). The necessity of expanding conventional technology adoption models by adding contextual factors that reflect the unique circumstances of developing nations has been highlighted by recent research (FakhrHosseini, et al., 2024). Technology adoption in healthcare settings with limited resources may be significantly influenced by factors like the availability of ICT infrastructure, trust in digital systems, privacy and security issues, and the presence of supportive legislative and regulatory frameworks (Djamba, Havyarimana, Mbambazi, & Niyongabo, 2025). However, there are still not many empirical research that incorporate these contextual factors into thorough models of e-health adoption, especially when it comes to Sub-Saharan Africa (Karamagi, et al., 2022). The current work creates and empirically tests a context-aware adoption model for e-health systems in the Democratic Republic of the Congo's healthcare system in order to close this research gap. The suggested model incorporates additional contextual constructs pertinent to fragile healthcare systems, such as ICT infrastructure, trust, privacy and security, and the policy and regulatory environment, while building upon the theoretical underpinnings of TAM and UTAUT.

The study attempts to provide a more thorough knowledge of the elements impacting healthcare workers' behavioral intention and actual usage of e-health systems by integrating technological, social, organizational, and contextual factors. This study makes three contributions. In the first place, it expands on current theories of technology adoption by putting forth an integrated, context-sensitive model that is suited to delicate healthcare settings. Second, it offers empirical data on the factors that influence healthcare workers in the Democratic Republic of the Congo to adopt e-health, a setting that is still underrepresented in studies on digital health. Third, the results provide useful information for system designers, healthcare organizations, and legislators who

want to encourage the long-term use of e-health in developing nations.

The remainder of this paper is organized as follows. The next section reviews the relevant literature on e-health systems and technology adoption models. The third section presents the research model and hypotheses. The fourth section describes the research methodology and data analysis procedures. The fifth section reports the empirical results, followed by a discussion of theoretical and practical implications. The paper concludes with recommendations and directions for future research

Literature Review

E-Health Systems and Digital Health Transformation

Globally, healthcare systems have seen a dramatic transformation due to the quick development of information and communication technologies (Dhindsa, Narang, & Choudhary, 2013).Healthcare modernization has been greatly aided by e-health systems, which are widely described as the use of digital technologies to enhance healthcare services, information exchange, and medical decision-making. Electronic health records (EHRs), telemedicine platforms, health information exchanges, mobile health applications, and clinical decision support systems are just a few of the many technologies that are included in these systems (Eysenbach, 2023) (Barbarella, Melchiorre, Quattrini, Papa, & Lamura, 2022). When used properly, e-health technologies can promote evidence-based medical practices, improve patient outcomes, increase healthcare efficiency, and make it easier for healthcare professionals to share data (Vest, 2010) (Barlow, Bayer, & Curry, 2006).

Governments and international organizations have been pushing digital health initiatives more and more in recent years as a way to improve healthcare delivery, especially in low- and middle-income nations (Raynaud, 2022).E-health technology can assist in addressing enduring issues including fragmented health information systems, a lack of healthcare experts, and restricted access to healthcare services (Maita, et al., 2024). Nevertheless, despite these possible advantages, e-health system adoption and implementation are still inconsistent, especially in poor nations where institutional, technological, and structural barriers frequently impede digital change (Danso, Asagba, Yarhere, Adumattah, & Amoaful, 2024).

Unreliable ICT infrastructure, low digital literacy among healthcare workers, inadequate funding, and weak governance frameworks are some of the extra issues that healthcare systems in unstable or resource-constrained situations must deal with (BOORE, 2018). The adoption and efficient use of digital health technologies are greatly impacted by these contextual limitations. As a result, studying the factors that promote or impede the adoption of e-
health in these settings has grown in importance within the fields of information systems and health informatics (Djamba, Havyarimana, Mbambazi, & Niyongabo,2025).

Technology Adoption Models in Information Systems Research

In the subject of information systems, technology adoption has been extensively

researched using a variety of theoretical frameworks that aim to explain how people and organizations accept and use new technologies. A few of these frameworks have become well-known because of their robust empirical support and broad applicability in various fields (James & Patricia, 2017).

The Theory of Reasoned Action (TRA), one of the first theoretical stances, contends that attitudes and subjective norms shape behavioral intention, which in turn shapes individual behavior (Ajzen & M. Fishbein, 1980:). Perceived behavioral control was added as a further factor influencing behavioral intention by the Theory of Planned Behavior (TPB), which built on this foundation (Taylor S. & Todd, 1995).

The Technology Acceptance Model (TAM) is one of the most important frameworks for researching technology acceptance in the field of information systems (Ajzen I. a., 1980). According to TAM, users' views toward a technology and, eventually, their propensity to use it are determined by two fundamental beliefs: perceived usefulness and perceived ease of use. The paradigm has been expanded over time and used in a variety of technologies, such as digital services, mobile applications, and healthcare information systems (F. Davis, 1989).

The Unified Theory of Acceptance and Use of Technology (UTAUT) is another popular framework that combines components from several adoption theories to offer a thorough explanation of technology acceptance behavior (A. Narh, James, & Patricia, 2012). UTAUT identifies four main determinants of behavioral intention and technology use: performance expectancy, effort expectancy, social influence, and facilitating conditions. The model has been widely used in healthcare settings to examine the adoption of telemedicine systems, electronic medical records, and other digital health technologies (A. Narh, James, & Patricia, 2012). While TAM and UTAUT have shown strong explanatory power, researchers are increasingly realities of technology adoption in developing nations, where institutional and environmental factors frequently play a significant role.

2.2.1 Technology Acceptance Model

The Technology Acceptance Model (TAM) is one of the most often applied theories in the healthcare sector, according to numerous research (S. Ekaimi, P. Utomo, D. Gunawan, S. Jimmy, & M. Christian, 2024). In addition to identifying the elements influencing technology adoption, this theory attempts to predict how new information systems and technologies will be used and accepted by society (F. Davis, P. Bagozzi, & P. Warshaw, 1989). The TAM has emerged as the main framework commonly used in technology and Internet of Things (IoT) research, according to Kamal and other authors (A., M. Shafiq, & P. Kakria, 2020) (Djamba & Irene, 2024). Additionally, it is frequently employed in research examining the relationship between technology and personal intents and behaviors (A., M. Shafiq, & P. Kakria, 2020).

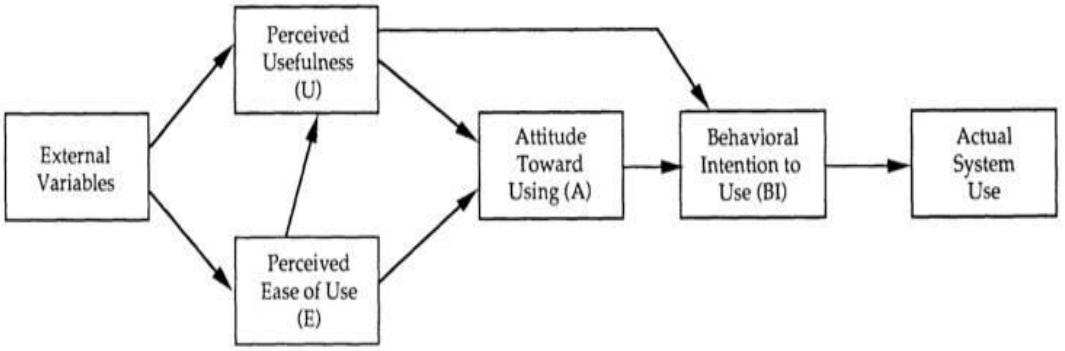

Fig. 1: TAM adapted from (F. Davis, P. Bagozzi, & P. Warshaw, 1989).

E-health systems, such as electronic health records (EHR), telemedicine platforms, mobile health applications, and hospital information systems, require active acceptance by both healthcare professionals and patients. Despite the potential benefits of these technologies, their implementation often encounters resistance due to usability issues, lack of training, and organizational constraints (Krisdina, Nurhayati, & Nugraheni, 2022).

TAM provides a valuable framework for understanding these challenges by emphasizing users' perceptions rather than purely technical aspects. When healthcare professionals perceive e-health systems as useful for improving patient care and easy to use within their workflow, they are more likely to adopt and continuously use such systems (Ráti & Ildikó, 2023).

According to Zoccarato and others authors (Zoccarato, Manzoni, Minotti, Lettieri, & Boaretto, 2024), there are a number of functional, psychological, and rational reasons why Italians have had trouble using the Dexcom ONE blood sugar monitor. This gadget, which can monitor blood sugar levels daily and provide technological solutions for daily diabetes management, was created for people who have trouble controlling their blood sugar levels because diabetes and its many complications are always among the most serious issues that arise globally. However, despite all of the benefits it provides to the target audiences, it still faces obstacles to social acceptance, including the equipment's technological design and the psychological characteristics of the patients. In order to determine the factors influencing the adoption of new technologies, the TAM theory was applied in this study. To get a trustworthy outcome, the authors integrated a number of elements into the model. They included subjective criteria in addition to the fundamental TAM theory variables of perceived utility and perceived ease of use, along with additional elements including glucose data visibility, trend arrows, alerts, stigma, and trust. Additionally, they included control variables to the model, including age, gender, the type of diabetes, the presence of caregivers, and health literacy.

They used questionnaires to collect data from 157 respondents who had been using Dexcom ONE for at least a month in order to ascertain the influence of psychological factors, functional elements, and rational conceptions on technology adoption. They found a strong link between reasonable thinking and the desire to employ CGM technology after analyzing the data using the SPSS

program. This finding highlights the critical role physicians play in encouraging the use of CGM technology. In addition to physicians, manufacturers, patient groups, and healthcare providers all play a critical role in ensuring that CGM devices are effectively utilized and accepted by diabetics.

The utility of teleconsultation during the COVID-19 pandemic was examined by Ekaimi (Ekaimi, et al., 2024). The rapid spread of the virus accelerated the adoption of teleconsultation technology. It was believed that employing teleconsultation instead of regularly scheduling in-person sessions could stop the COVID-19 virus from spreading due to the development of teleconsultation, which tries to reduce the likelihood of face-to-face encounters. However, the rapid expansion of teleconsultation and the pandemic presented many parties with serious difficulties, such as governments managing legal matters, healthcare providers lacking the required tools and training, and patients being wary of virtual therapy replacing in-person appointments .Thus, the purpose of this study was to investigate patient behaviors related to teleconsultation adoption and use during the pandemic, with an emphasis on determining the determinants influencing adoption. They included two additional variables trust and privacy to their investigation in addition to the TAM hypothesis to ensure an accurate result. One hundred patients between the ages of twenty and forty who had a bachelor's degree in education and had utilized teleconsultation services at one of Indonesia's private hospitals during the pandemic in 2020 and 2021 filled out an on-site questionnaire that they created in order to collect data. After the data analysis, they observed a positive association between intention to use and perceived privacy, trust, and simplicity of use. These results lead them to conclude that patients generally find the program easy to use, but older patients (those 55 and older) require additional support and teaching. Because of their prior interactions with the hospital and their knowledge that they are dealing with qualified medical professionals, patients have faith in this technology. Patients with delicate diseases are often comfortable using the program because their medical records and consultation findings are kept current, despite their ongoing concerns about data security. Lastly, if patients find the app convenient, secure, and reliable for online consultations, they are more likely to utilize it.

Zin investigated how older Koreans used digital healthcare technologies (Zin, Kim, Kim, & I.F., 2023). Given the sizeable aging population in Korea, older folks need to become knowledgeable about the newest medical technologies in order to improve their safety. For instance, they might avoid mishaps by donning smart health watches, which would also make it simpler to keep an eye on senior citizens' health. The COVID-19 pandemic has caused a decrease in face-to-face meetings since the virus spreads through these kinds of encounters. The use of technology in the healthcare sector has greatly risen as it may considerably lower the risk of viral proliferation. However, older folks find it difficult to use technology due to physical limitations and a lack of technical knowledge. Understanding their viewpoints, attitudes toward developing technology, and readiness to employ the newest medical innovations is so crucial. It is also crucial to identify the obstacles to the use of digital healthcare technology. They therefore conducted study utilizing an enhanced Technology Acceptance Model, accounting for the COVID-19 pandemic, to assess the development and use of digital health and wrist-worn wearable devices among senior Koreans. They used the original

TAM theory in their investigation even though they felt it had limits for this type of research. They therefore added two new factors to the theory social effect and enabling conditions to account for various features. They developed a questionnaire for the target population, which consists of Busan residents 56 years of age and older, in order to gather data. A total of 170 responses were collected to examine the data. The analysis of the data revealed that perceived ease of use, perceived usefulness, and facilitating conditions all had a favourable influence on views on the adoption of digital health wearables. However, social influence had little effect on perceptions of these technologies. Their conclusion, which lends support to the larger TAM and is in line with previous study findings, is that a positive perspective is highly connected with the behavioural intention to utilise digital health wearables, implying that the more positively they perceive these technologies, the more likely they are to use them.

The application of artificial intelligence (AI) in the UAE healthcare industry was studied by Alhashmi and others authors (Alhashmi, Salloum, & Mhamdi, 2019). The UAE is putting a lot of attention on integrating AI to enhance its public healthcare system. Everyone involved patients, medical personnel, and others must have a high degree of acceptance of AI in order to guarantee the efficient use of healthcare technology. The ETAM theory, which is an expansion of the TAM theory with additional variables to fit the research situation, was applied in this study. They added four more variables to the TAM theory: managerial factors, organizational factors, strategic factors, and IT infrastructure factors, in addition to the original TAM constructs of perceived ease of use, perceived usefulness, attitude toward use, and behavioral intention to use. The ETAM theory is composed of these combinations of variables. They contend that the inclusion of these extra variables in the ETAM makes it possible to identify critical success factors (CSFs) associated with the adoption of AI in the healthcare sector. This study sought to determine how effectively the ETAM forecasts the successful implementation of AI in healthcare. They created a survey to gather information, and 13 medical facilities in Dubai provided 53 answers, including those from IT and medical personnel. Following data analysis, they found that every variable was supported, except for strategic considerations, which were negatively correlated with perceived ease of use. This means that healthcare project managers have to consider these external challenges when improving TAM structures for AI implementation.

2.2.2 Unified Theory of Acceptance and Use of Technology

IT-related research often uses the UTAUT theory in addition to the TAM theory. Unlike the TAM, the UTAUT is a theory composed of eight distinct independent acceptance theories (Venkatesh, Morris, Davis, & Maheshwari, 2003). The UTAUT simplifies difficult technology acceptance tests and provides a thorough understanding of technology adoption in the healthcare sector by combining various theories into a single model (Venkatesh, Morris, Davis, & Maheshwari, 2003).

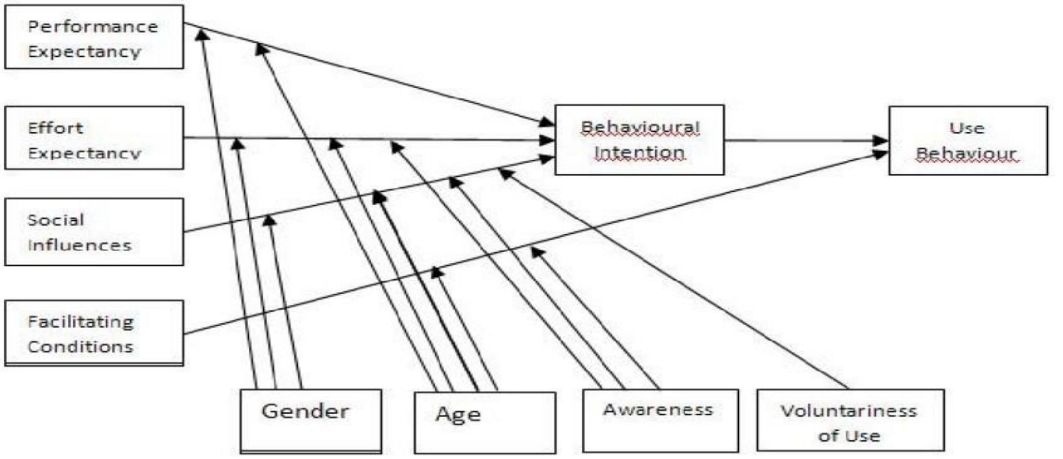

Fig 2: The UTAUT Model (A. Narh, James, & Patricia, 2012)

Because of the serious flaws in some of the theories and models used to analyze and assess how people embrace and accept new technologies, Venkatesh developed the UTAUT model in an attempt to develop a more thorough model for understanding technology usage and adoption.

After studying eight models of technology acceptance and use, Venkatesh and his colleagues selected a subset of 32 structures that they discovered to constitute UTAUT. Venkatesh and his associates used information from two polls as well as earlier TAM research to create, validate, and test a new model (A. Narh, James, & Patricia, 2012).

The behavioral goal and technology utilization in UTAUT are determined by output expectation, effort expectation, societal impact, and enabling conditions (Fig 2). The UTAUT construct of encouraging conditions, according to Venkatesh (A. Narh, James, & Patricia, 2012), captures components within effort anticipation constructs that are pertinent to ICT infrastructure. According to UTAUT, the presence of both performance expectation and effort expectation constructions makes promoting conditions in the prediction of intention insignificant.
Drawing on the earlier discourse on the technological model, scholars have expanded several models by incorporating security considerations as variables impacting the adoption of e-health The application of the Unified Theory of Acceptance and Use of Technology (UTAUT) in e-health within the Democratic Republic of the Congo (DRC) presents a significant opportunity to enhance healthcare delivery. UTAUT identifies key factors influencing technology acceptance, which can be tailored to the unique challenges faced in the DRC's healthcare system. The successful integration of e-health technologies is primarily driven by Performance Expectancy, which refers to the degree to which users believe that using a specific system will help them attain gains in job performance or health management. When medical professionals and patients perceive these digital tools as beneficial for improving healthcare outcomes and efficiency, the likelihood of adoption increases significantly (Fettermann & Calegari, 2024) . This perception of utility acts as a foundational motivator for transitioning from

traditional methods to digital platforms.Beyond perceived benefits, Effort Expectancy plays a vital role in determining how readily a system is embraced. This factor focuses on the ease of use associated with e-health systems; if a platform is viewed as overly complex or counterintuitive, users are often deterred. However, the impact of this barrier can be mitigated through comprehensive training and ongoing technical support, which enhance the user's confidence and simplify the interaction with the technology (Feng & Haridas, 2025).The social environment also serves as a powerful catalyst for change through Social Influence. The acceptance of e-health among medical professionals is often driven by the attitudes and endorsements of their peers and healthcare leaders. When influential figures within the medical community promote and model the use of digital health tools, it creates a professional standard that encourages others to follow suit (Fettermann & Calegari, 2024) .Finally, the practical success of implementation depends heavily on Facilitating Conditions. These represent the structural support systems available to the user, including the necessary technical infrastructure, financial resources, and specialized assistance. Without these critical elements in place, even the most motivated users may find it impossible to sustain the use of e-health technologies over the long term (Feng & Haridas, 2025).

E-Health Adoption in Healthcare Systems

A complex interaction of organizational, human, and technological factors influences the adoption of e-health technology in healthcare organizations (Aamir, Ali, Boulos, Anjum, & Ishaq, 2017). The factors influencing healthcare workers' acceptance of the e-health system have been examined in a number of research using technology adoption models (A. Narh, James, & Patricia, 2012).

One of the most important indicators of technology adoption has been repeatedly found to be perceived utility. When healthcare personnel think that e-health systems would improve their work performance, increase clinical efficiency, or facilitate patient care, they are more likely to use them (Ekaimi, et al., 2024). In a similar vein, users' opinions of digital health systems are significantly influenced by perceived simplicity of use. User-friendly and intuitive systems have a higher chance of being adopted and incorporated into standard medical procedures (Feng & Haridas, 2025).

In healthcare settings, peer recommendations, leadership backing, and professional norms can all have a big impact on adoption decisions. Furthermore, the successful application of health information systems depends on enabling factors including the availability of technical assistance, training courses, and sufficient infrastructure (Djamba, Havyarimana, Mbambazi, & Niyongabo,2025).

Even though the amount of research on e-health adoption is increasing, most of it focuses on industrialized nations or healthcare settings with advanced technology. On the other hand, there is little empirical data on the factors influencing the adoption of digital health in unstable healthcare systems with institutional and structural limitations (K. Josue, Vincent. Havyarimana, Businge. Pheliix, & Julius. Niyongabo, 2026).

Contextual Determinants of E-Health Adoption in Developing Countries

The significance of contextual factors in influencing technology adoption behavior, especially in developing nations, has been highlighted by recent studies (An, et al., 2024). It is impossible to properly comprehend technological acceptability in fragile healthcare systems without taking into account the larger environmental circumstances surrounding the implementation of digital health systems.

ICT infrastructure, which includes network capacity, hardware availability, internet access, and electricity dependability, is one important factor. Inadequate infrastructure severely restricts the usability and accessibility of digital health technology in many developing nations (Kovačić M., 2022).

Trust in digital systems is another crucial component, especially when it comes to patient data integrity and confidentiality. Patients and healthcare providers need to have faith that electronic systems will safeguard private medical data and adhere to legal and ethical requirements (Velmurugan, Prakash, Neelakandan, & Radhakrishnan, 2024).

Concerns about security and privacy are closely linked to trust and have grown in significance as healthcare data is exchanged and digitalized across interconnected systems. Healthcare practitioners may be deterred from implementing digital health technologies by inadequate cybersecurity measures and data protection laws.

Lastly, the regulatory and policy landscape has a significant impact on how well or poorly digital health is implemented. For health information systems to be interoperable, standardized, and governed, clear policies, national e-health initiatives, and regulatory frameworks are crucial (Chan, et al., 2025).

Research Gap and Conceptual Framework

There are still a number of gaps in the literature, despite the fact that earlier research has offered insightful information about the factors influencing technology adoption in healthcare. First, a lot of research that has already been done mostly relies on conventional adoption models like TAM and UTAUT without sufficiently taking into account contextual elements that are especially important in delicate healthcare settings. Second, despite the increasing significance of digital health projects in the region, there is still a dearth of empirical research on e-health adoption in Sub-Saharan Africa.

To address these constraints, the present work presents a context-aware adoption model for e-health systems that incorporates fundamental constructs from TAM and UTAUT with additional contextual determinants important to emerging healthcare systems. ICT infrastructure, trust, privacy and security, and the legal and policy landscape are some of these contextual factors.

By combining individual, organizational, and contextual factors, the proposed framework aims to provide a more comprehensive understanding of the determinants influencing healthcare professionals' behavioral intention and actual use of e-health systems in the Democratic Republic of Congo.

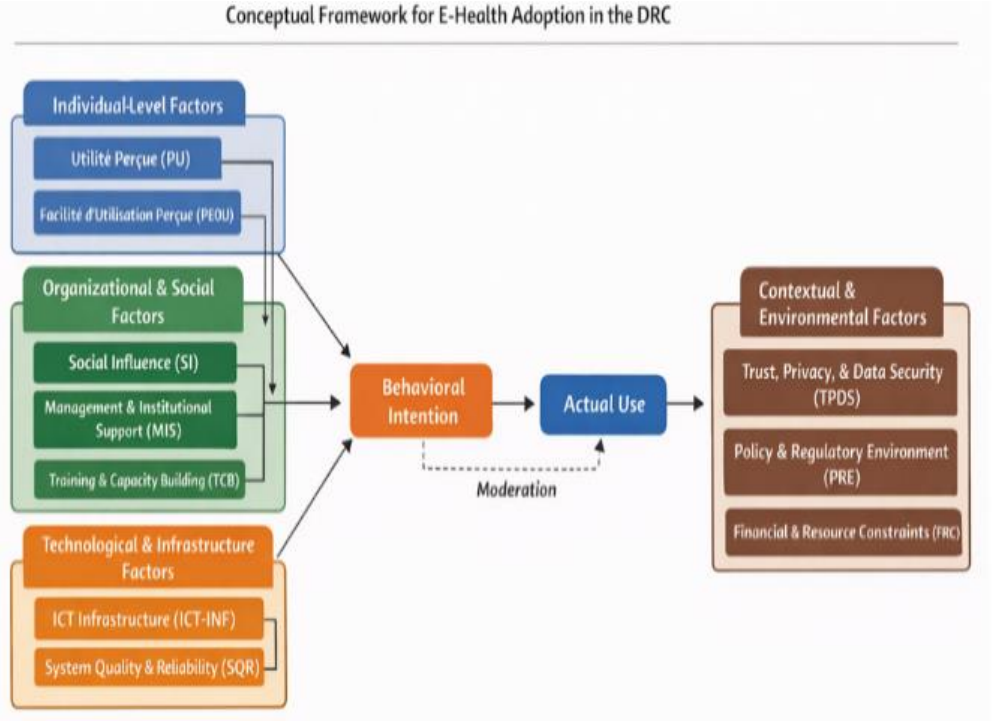

Fig 3: Conceptual framework for e-health adoption based on a mixed TAM–UTAUT model.

Methodology

Research Design

The factors impacting the adoption of e-health systems in the Democratic Republic of the Congo's (DRC) healthcare sector are examined in this study using a quantitative research methodology (Mbanaso, Abrahams, & Okafor, 2023). Because it enables the empirical examination of connections between variables derived from well-established theories of technology adoption, a quantitative design was deemed appropriate. Data from healthcare professionals were gathered at a single point in time using a cross-sectional survey design. The suggested research model incorporates additional contextual elements pertinent to fragile healthcare environments while integrating constructs from well-known theories of technology acceptance, such as the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM). The conceptual framework examines how technological, social, organizational, and contextual factors influence healthcare professionals' behavioral intention to adopt e-health systems, which subsequently affects their actual use of these systems (Glanz & Bishop, 2018).

Research Model and Hypotheses

By combining conventional technology acceptance dimensions with contextual factors pertinent to evolving healthcare systems, the suggested study model seeks to explain the adoption of e-health systems. The following important constructs are part of the model:Perceived Usefulness (PU),Perceived Ease of Use

(PEOU),Social Influence (SI),Facilitating Conditions (FC),Trust in E-health Systems (TR),Privacy and Security Concerns (PS),ICT Infrastructure (ICTI),Policy and Regulatory Support (PRS),Behavioral Intention to Use (BI),Actual System Use (AU) **(Luo, 2023)**.

Based on the theoretical framework, several hypotheses were formulated to test the relationships between these constructs. The model assumes that perceived usefulness, perceived ease of use, social influence, facilitating conditions, trust, privacy and security perceptions, ICT infrastructure, and policy support influence healthcare professionals' behavioral intention to adopt e-health systems, which in turn affects actual system use.

3.3 Data Collection

A standardized questionnaire was used to gather data from medical professionals employed by various healthcare facilities in the Democratic Republic of the Congo. Physicians, nurses, healthcare administrators, medical technicians, and health information managers were among the target responses. Because they are the main users of digital health systems in healthcare companies, these respondents were chosen.

Depending on accessibility and the availability of infrastructure at healthcare facilities, the questionnaire was distributed by both online and Kobocollect-based surveys. The questionnaire was administered through both online and paper-based surveys, depending on accessibility and infrastructure availability within healthcare facilities. Prior to the full survey deployment, the questionnaire was pre-tested with a small group of healthcare professionals to ensure clarity, relevance, and reliability of the measurement items.
Participation in the study was voluntary, and respondents were informed about the purpose of the research and the confidentiality of their responses.

3.4 Sampling Strategy

To determine an appropriate sample size for the quantitative phase of the study, Slovin's formula was applied. This formula is suitable when the population size is known and when the researcher seeks to obtain a representative sample with a specified margin of error (Anugraheni, Izzah, & Hadi, 2023).

Fig 4: Slovin's Formula:

Where:

$$n = \frac{N}{1 + N(e^2)}$$

- **n** = r
- **N** = population size
- **e** = margin of error

For this study:

- N=23,000N = 23,000N=23,000 (estimated number of healthcare professionals in North Kivu)
- e=0.05e = 0.05e=0.05 (5% margin of error)

Fig 5: Calculation

$$n = \frac{23,000}{1 + 23,000(0.05^2)}$$

$$n = \frac{23,000}{1 + 23,000(0.0025)}$$

$$n = \frac{23,000}{58.5}$$

$$n \approx 393$$

This sample size aligns with methodological recommendations for studies based on TAM and UTAUT, which typically require between 200 and 400 respondents to ensure sufficient statistical power.

3.5 Measurement Instruments

The questionnaire was designed based on established e-health adoption theories and included both demographic and construct-based items. The demographic section captured respondents' background information such as gender, age group, professional role, years of experience, and type of health facility. The second section focused on core constructs related to e-health adoption, including perceived usefulness, perceived ease of use, attitude toward e-health, behavioral intention to use e-health systems, organizational readiness, infrastructure availability, and perceived security and privacy.

All construct-based items were measured using a five-point Likert scale ranging from "strongly disagree" to "strongly agree," allowing for quantitative assessment of respondents' perceptions and attitudes. After data collection, the questionnaires were screened for completeness and consistency. Valid responses were coded and entered into SPSS for analysis. The collected dataset provided sufficient information to conduct reliability testing, descriptive analysis, and inferential statistical procedures

3.6 Data Analysis

The analysis of the data was completed using structural equation modeling (SEM), a reliable method that allows for the simultaneous examination of the intricate relationships between the many components of the proposed research model (Hair, Risher, Sarstedt, & Ringle, 2019). In accordance with the methodological guidelines of the study, the analysis was organized into two stages, starting with the assessment of the measurement model and ending with the examination of the structural model (Bagozzi & Yi, 1988).

Before testing the hypotheses, the first phase of the analysis was evaluating the measurement model to ensure the validity and reliability of the constructs. The Cronbach's alpha and the composite reliability (CR) were calculated to assess the internal coherence of the data. In accordance with the criteria established by Hair et al., a minimum value of 0.70 was maintained for these two indicators in order to verify the measure's robustness (Hair, Black, Babin, & Anderson, 2019).

The model's validity was then examined through two lenses: discriminant validity and convergent validity. Examining the variance average extracted (AVE), which requires a minimum value of 0.50 to indicate that the construct explains more of the variance of its indicators, confirmed the convergent validity (Fornell & Larcker, 1981). Finally, the discriminant validity was confirmed by applying the Fornell-Larcker criterion and examining the increased charges (cross-loadings), ensuring that each construction is statistically different from the other variables in the model.

3.7 Ethical Considerations

Ethical principles were carefully considered during the research process. Participation in C before completing the questionnaire. No personal identifying information was collected, ensuring the anonymity and confidentiality of participants. The data collected were used solely for academic research purposes (Nii Laryeafio & Ogbewe, 2023) (HWANG, 2023).

3.8 Summary of the Methodology

The factors of e-health adoption among healthcare professionals in the Democratic Republic of the Congo were investigated in this study using a quantitative survey-based methodology. The study offers a strong empirical foundation fo`r examining the environmental and technological elements influencing the adoption of e-health systems in delicate healthcare settings by fusing structural equation modeling techniques with verified assessment scales.

Results

4.1 Descriptive Statistics

A total of 400 questionnaires were distributed to healthcare professionals working in various healthcare institutions in the Democratic Republic of Congo. After data screening and removal of incomplete responses, 393 valid responses were retained for analysis.

The respondents included physicians, nurses, healthcare administrators, and health information managers who are directly involved in healthcare service delivery and may interact with digital health technologies. The sample provides a representative overview of healthcare professionals potentially exposed to e-health systems within the Congolese healthcare sector.

Table 1: Distribution of Respondents by Gender

	Frequency	Percentage	Cumulative Percent
I prefer not to say.	1	,3	,3
Female	147	37,4	37,7
Male	245	62,3	100,0
Total	393	100,0	

The table presents the gender distribution of the respondents involved in the study. A total of 393 respondents participated in the survey. Among them, 245 respondents (62.3%) were male, while 147 respondents (37.4%) were female. Only one respondent (0.3%) preferred not to disclose their gender.

The results indicate that the study sample was male-dominated, with nearly two-thirds of the respondents being men. This gender imbalance may reflect the existing workforce composition in the healthcare and health information technology sectors in the Democratic Republic of Congo, where male participation remains higher, particularly in technical and administrative roles. However, the presence of a substantial proportion of female respondents ensures that perspectives from both genders are represented in the analysis.

Overall, the gender distribution is adequate for the purposes of this study and provides a reasonable basis for analyzing e-health adoption and information systems architecture across different respondent groups.

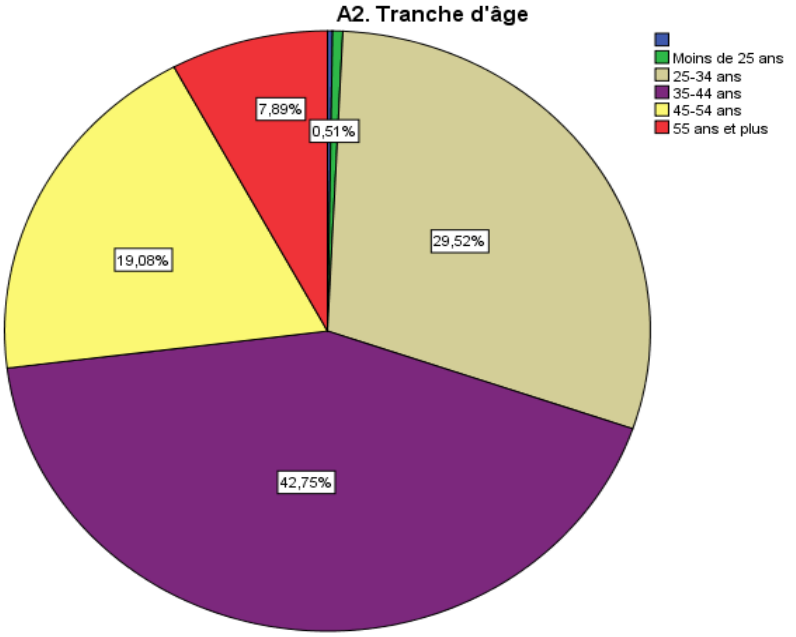

Fig 6: Distribution of Respondents by Age Group

The pie chart illustrates the age distribution of respondents who participated in the study on e-health adoption. The results show that the largest proportion of respondents falls within the 35–44 years age group, accounting for 42.75% of the total sample. This is followed by respondents aged 25–34 years, who represent 29.52% of the participants. Together, these two age groups constitute more than 72% of the respondents, indicating that the study primarily involved individuals in their most active professional years.

Respondents aged 45–54 years make up 19.08% of the sample, while those aged 55 years and above account for 7.89%. These groups represent experienced

professionals who may play key decision-making or supervisory roles within healthcare institutions. In contrast, respondents under 25 years are minimally represented, with only 0.51%, suggesting limited participation from younger individuals, possibly due to lower involvement in formal healthcare or health information system roles.

Overall, the age distribution indicates that the survey largely captured the perspectives of mature and professionally active respondents, which is appropriate for assessing e-health implementation and adoption, as these individuals are more likely to interact with health information systems and influence their use within healthcare facilities.

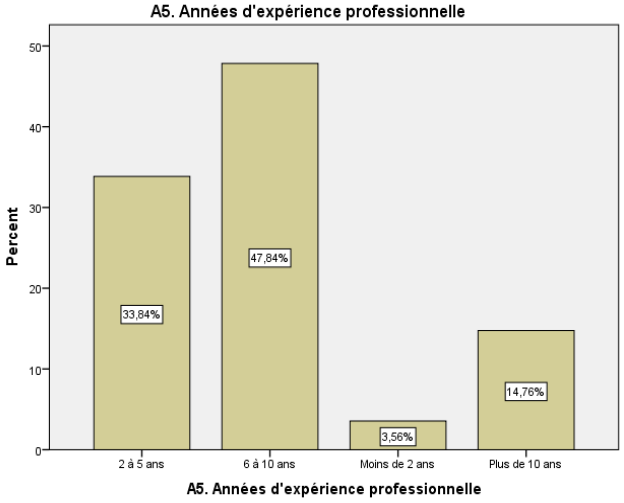

Fig 7: Distribution by Years of Experience

The figure illustrates the distribution of respondents according to their years of professional experience. The results show that the largest proportion of respondents, 47.84%, have 6 to 10 years of professional experience. This indicates that nearly half of the participants are mid-career professionals, who are likely to possess substantial practical knowledge of healthcare workflows and exposure to both traditional and digital health systems.

Respondents with 2 to 5 years of experience represent the second largest group, accounting for 33.84% of the sample. This group reflects early-career professionals who may be more adaptable to new technologies and innovative practices such as e-health solutions. In contrast, only 3.56% of respondents have less than 2 years of experience, suggesting limited representation of newly recruited healthcare workers in the study.

Finally, 14.76% of respondents report having more than 10 years of professional experience. This group brings valuable long-term institutional knowledge and may provide insights into organizational change and resistance to technology adoption. Overall, the distribution indicates that the majority of respondents have moderate to extensive professional experience, which enhances the reliability of the findings related to e-health adoption, as participants are sufficiently experienced to

evaluate the usefulness, challenges, and implications of implementing e-health systems within the healthcare sector.

Table 2: Descriptive Statistics of Study Variables

Construct	*Mean*	*Standard Deviation*
Perceived Ease of Use (PEOU)	4,39	0.693
Perceived Usefulness (PU)	4.31	0.692
Social Influence (SI)	4.39	0.643
Facilitating Conditions (FC)	4.44	0.684
ICT Infrastructure (ICTI)	4.46	0.725
Trust, Privacy and Security (TPS)	4.43	0.654
Policy and Regulatory Environment (PRE)	4.24	0.701
Behavioral Intention (BI)	4.44	0.636
Actual Use (AU)	4.41	0.731

The results indicate generally positive perceptions toward the use of e-health technologies among healthcare professionals, although some contextual factors such as Policy and Regulation remain moderate.

4.2 Factor Analysis of Variables for the Research Model

Factor analysis was conducted to examine the underlying structure of the variables included in the research model and to assess construct validity. This analysis aimed to verify whether the observed variables adequately represent their respective latent constructs within the e-health adoption framework.

An exploratory factor analysis (EFA) was performed using principal component analysis with varimax rotation. The results revealed a clear factor structure, with all measurement items loading significantly on their respective constructs. Factor loadings exceeded the recommended threshold of 0.5, indicating strong relationships between observed variables and their underlying latent factors.

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was found to be acceptable, confirming the suitability of the data for factor analysis. Additionally, Bartlett's test of sphericity was statistically significant, indicating that correlations among variables were sufficient to justify the application of factor analysis.

The extracted factors correspond to the key constructs of the research model, including perceived usefulness, perceived ease of use, social influence, facilitating conditions, ICT infrastructure, trust, privacy and security, policy environment, behavioral intention, and actual use.

These results confirm the validity of the measurement model and support the inclusion of these constructs in subsequent statistical analyses.

Table 3: Factor Loading

	Component Matrix
PERCEIVED EASE OF USE	
PEOU1	,785
PEOU2	,780
PEOU3	,771
PEOU	,815
PERCEIVED USEFULNESS(PU)	
PU1	,770
PU2	,728
PU3	,740
PU4	,764
FACILITATING CONDITIONS(FC)	
FC1	,822
FC2	,790
FC3	,744
FC4	,654
ICT INFRASTRUCTURE (ICT)	
ICT1	,803
ICT2	,811
ICT3	,806
ICT4	,823
SOCIAL INFLUENCE(SI)	
SI1	,728
SI2	,784
SI3	,785
SI4	,767
TRUST, PRIVACY, AND SECURITY(TPS)	
TPS1	,796
TPS2	,760
TPS3	,779
TPS4	,758
POLICY AND REGULATORY ENVIRONMENT(PRE)	
PRE1	,597
PRE2	,678
PRE3	,670
BEHAVIORAL INTENTION(BI)	
BI1	,804
BI2	,786
BI3	,736
BI4	,796
ACTUAL USE(AU)	
AU1	,819
AU1	,797
AU3	,766

	Component Matrix
AU4	,703

The findings of this study provide strong empirical support for the proposed research model explaining e-health adoption among healthcare professionals in the Democratic Republic of the Congo. Overall, the results indicate that both technological and organizational factors play a critical role in shaping users' perceptions and behavioral intentions toward e-health systems. The factor analysis confirmed that all measurement items loaded adequately on their respective constructs, demonstrating good construct validity and reinforcing the robustness of the model. High loadings for Perceived Ease of Use (PEOU) suggest that healthcare professionals generally find e-health systems easy to learn, understand, and integrate into their daily work, which aligns with the Technology Acceptance Model (TAM) and emphasizes usability as a key determinant of adoption. Similarly, Perceived Usefulness (PU) emerged as a strong construct, indicating that respondents believe e-health systems enhance productivity, improve healthcare service quality, and increase work efficiency, thereby reinforcing the instrumental value of digital health technologies.

Beyond individual perceptions, organizational and environmental factors also showed substantial influence. Facilitating Conditions (FC) and ICT Infrastructure (ICT) recorded high factor loadings, highlighting the importance of reliable internet connectivity, availability of digital devices, stable power supply, adequate technical support, and training. These findings underscore that even when users have positive attitudes toward e-health, adoption remains highly dependent on the availability of enabling resources. Social Influence (SI) further contributed significantly, demonstrating that encouragement from colleagues, institutional leadership, and health authorities positively shapes users' willingness to adopt e-health systems. This reflects the collectivist nature of professional decision-making within healthcare environments in the DRC.

Moreover, the constructs of Trust, Privacy, and Security (TPS) and Policy and Regulatory Environment (PRE) emphasize the broader systemic context of e-health adoption. Strong loadings for TPS indicate that confidence in data security, patient confidentiality, and system reliability is a critical prerequisite for acceptance. Meanwhile, although PRE exhibited relatively moderate loadings compared to other constructs, the results still suggest that supportive policies, legal frameworks, and political commitment play an important role in legitimizing and sustaining e-health initiatives. Finally, Behavioral Intention (BI) showed consistently strong loadings, confirming that respondents demonstrate a clear intention to use e-health systems, which reflects the combined influence of individual, organizational, and environmental determinants identified in the model.

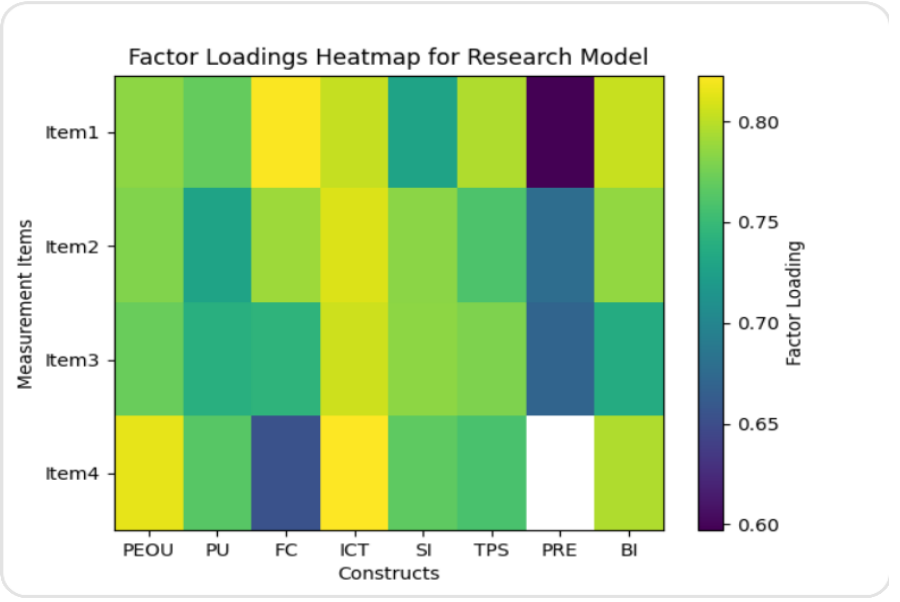

Fig 8: Factor Loading Heatmap for Research Model

The fig. 8 illustrates strong factor loadings across all constructs, confirming convergent validity and the robustness of the measurement model

4.3 Interpretation of KMO and Bartlett's Test of Sphericity

Table 4: Interpretation of KMO and Bartlett's Test of Sphericity

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,969
Bartlett's Test of Sphericity	Approx. Chi-Square	1278 1,56 9
	df	595
	Sig.	,000

The suitability of the dataset for factor analysis was assessed using the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity. The KMO value obtained was 0.969, which far exceeds the minimum acceptable threshold of 0.50 and falls within the "excellent" range. This result indicates that the correlations among the variables are sufficiently compact and that the sample size is highly adequate for conducting factor analysis. In practical terms, it confirms that the observed variables share enough common variance to justify the extraction of underlying latent factors. Bartlett's Test of Sphericity further supports the appropriateness of factor analysis, as the test was found to be statistically significant (Approx. Chi-square = 12,781.569, df = 595, $p < 0.001$). This significant result rejects the null hypothesis that the correlation matrix is an

identity matrix, thereby confirming the existence of meaningful relationships among the variables. Consequently, the data structure is suitable for identifying latent constructs within the research model. Overall, the combined results of the KMO measure and Bartlett's Test provide strong empirical justification for proceeding with factor analysis. These findings validate the methodological rigor of the study and confirm that the extracted factors reliably represent the underlying constructs influencing e-health adoption in the Democratic Republic of the Congo.

4.4 Correlation between E-Health Adoption and Influencing Factors

To test the relationships, correlation and regression analysis were used. While the descriptive and factor analyses confirm the validity and internal consistency of the measurement model, they do not explain the strength or direction of relationships between the independent variables and e-health adoption outcomes. Therefore, to move beyond measurement validation and examine causal relationships, the next stage of analysis employs regression analysis and regression. This step aims to determine the extent to which Perceived Ease of Use, Perceived Usefulness, Social Influence, Facilitating Conditions, ICT Infrastructure, Trust, and Policy and Regulatory Environment significantly predict Behavioral Intention and Actual Use of e-health systems. The regression results will provide empirical evidence on the most influential determinants of e-health adoption in the DRC, thereby addressing the study's research hypotheses and objectives.

In this study, Behavioral Intention (BI) is used as the dependent variable to measure e-health adoption. This choice is justified by the fact that e-health systems in the Democratic Republic of Congo are still in varying stages of implementation, and actual usage may be constrained by infrastructural and organizational limitations. Behavioral intention is therefore considered a more appropriate indicator of adoption, as it captures healthcare professionals' readiness and willingness to use e-health systems once enabling conditions are met.

Table 4: Pearson's Correlation Coefficient

Correlations			
			Behavior Intention
PEOU_mean	Corrélation de Pearson	,794**	Strong positive correlation
	Sig. (bilatérale)	,000	
	N	393	
PU_mean	Corrélation de Pearson	,739**	Strong positive correlation
	Sig. (bilatérale)	,000	
	N	393	
SI_mean	Corrélation de Pearson	,797**	Strong positive correlation
	Sig. (bilatérale)	,000	
	N	393	
FC_mean	Corrélation de Pearson	,750**	Strong positive correlation
	Sig. (bilatérale)	,000	

	N	393	
ICT_mean	Corrélation de Pearson	,804**	Strong positive correlation
	Sig. (bilatérale)	,000	
	N	393	
IPS_mean	Corrélation de Pearson	,759**	Strong positive correlation
	Sig. (bilatérale)	,000	
	N	393	
PRE_mean	Corrélation de Pearson	,644**	Strong positive correlation
	Sig. (bilatérale)	,000	
	N	393	
AU_mean	Corrélation de Pearson	,794**	Strong positive correlation
	Sig. (bilatérale)	,000	
	N	393	

The Pearson correlation analysis reveals statistically significant positive relationships between Behavioral Intention and most of the proposed determinants. Trust, Privacy and Security ($r = 0.769$, $p < 0.001$) and ICT Infrastructure ($r = 0.669$, $p < 0.001$) exhibit the strongest associations with behavioral intention, highlighting their critical role in e-health adoption. Perceived Usefulness, Social Influence, and Facilitating Conditions also demonstrate strong and significant correlations, supporting the theoretical assumptions of the research model. These findings justify the inclusion of all constructs in the subsequent regression analysis.

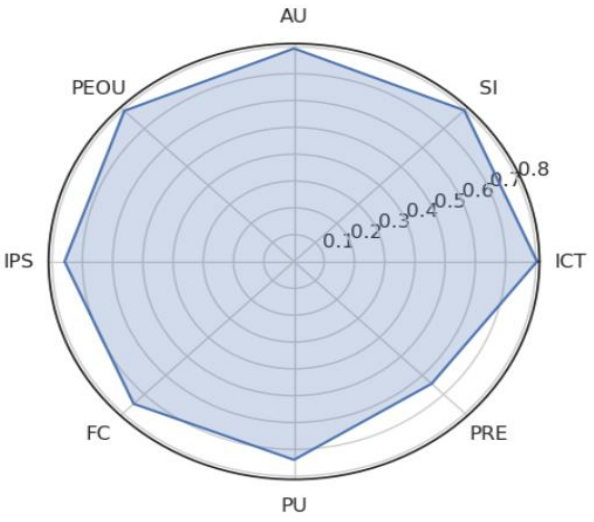

Fig 9: vertical heatmap of correlations with Adoption Intention

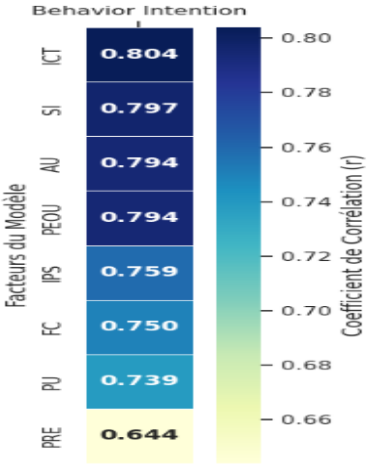

Fig 10: Radar Chart of correlations with Adoption Intention

The vertical heatmap (Fig 10) illustrates the strength of the correlations between each model factor and Behavioral Intention (BI) to adopt the e-health system. The factors are arranged in descending order, from the strongest to the weakest association.

Overall, the results indicate that all factors exhibit positive correlations with Behavioral Intention, suggesting that improvements in these constructs are associated with higher intention to adopt the system. Among the predictors, ICT shows the strongest correlation (r = 0.804), highlighting the critical role of information and communication technologies in shaping adoption intentions. This finding suggests that technological readiness, infrastructure availability, and digital competence are key determinants of e-health acceptance.

The next most influential factors are Social Influence (SI) (r = 0.797), Attitude toward Use (AU) (r = 0.794), and Perceived Ease of Use (PEOU) (r = 0.794). Their high correlation values indicate that both social environment and individual perceptions of usability strongly motivate users' willingness to adopt the system. The radar chart(Figure 31) provides a holistic visualization of the relative strength of all factors simultaneously. Each axis represents one construct, and the distance from the center reflects its correlation with Behavioral Intention.

The nearly circular shape of the polygon indicates that all variables contribute positively and relatively strongly to Behavioral Intention, with no factor showing a negligible effect. However, the outward extensions toward ICT, SI, AU, and PEOU confirm their dominant influence, as already observed in the heatmap.

The chart also reveals a gradual decline toward IPS, FC, and PU, followed by a noticeable inward contraction at PRE, emphasizing its comparatively lower contribution. This visual pattern highlights a hierarchy of influence among the predictors.
Importantly, the radar chart demonstrates that e-health adoption is a multidimensional phenomenon driven by a combination of technological, social,

cognitive, and contextual factors rather than a single determinant. The balanced distribution suggests that successful implementation strategies should address all dimensions simultaneously, with particular emphasis on strengthening technological infrastructure, enhancing usability, and leveraging social support mechanisms.

4.5 Reliability and Validity Assessment

The reliability and validity of the measurement model were evaluated before testing the structural relationships between constructs. Internal consistency reliability was assessed using Cronbach's Alpha and Composite Reliability (CR). Convergent validity was examined using Average Variance Extracted (AVE).

Table 5: Reliability and Convergent Validity

Construct	***Cronbach's Alpha***	***Composite Reliability***	***AVE***
PEOU	0.90	0.86	0.72
PU	0.88	0.84	0.68
SI	0.86	0.78	0.54
FC	0.87	0.80	0.56
ICTI	0.91	0.82	0.61
TPS	0.89	0.85	0.65
PRE	0.85	0.76	0.52
BI	0.88	0.88	0.74
AU	0.89	0.83	0.69

All Cronbach's alpha and composite reliability values exceed the recommended threshold of **0.70**, indicating good internal consistency. Furthermore, AVE values are above **0.50**, confirming convergent validity.

4.6 Structural Model Analysis

After confirming the adequacy of the measurement model, the structural model was assessed to evaluate the hypothesized relationships between constructs. The results of the structural equation modeling analysis are summarized in Table 4.

Table 6: Structural Model Results

Hypothesis	**Relationship**	**β**	**t-value**	**p-value**	**Result**
H1	PEOU → PU	0.52	8.41	<0.001	Supported
H2	PU → BI	0.36	6.12	<0.001	Supported
H3	PEOU → BI	0.18	2.91	0.004	Supported
H4	SI → BI	0.21	3.47	0.001	Supported
H5	FC → AU	0.24	3.26	0.002	Supported
H6	ICTI → AU	0.19	2.84	0.005	Supported
H7	TPS → BI	0.23	3.56	<0.001	Supported
H8	PRE → AU	0.16	2.41	0.016	Supported
H9	BI → AU	0.41	7.03	<0.001	Supported

The results show that perceived usefulness, perceived ease of use, social influence, and trust-related factors significantly influence healthcare professionals' behavioral intention to adopt e-health systems. Additionally,

facilitating conditions, ICT infrastructure, and the policy environment significantly influence the actual use of e-health systems.

4.7 Coefficient of Determination (R^2)

The explanatory power of the research model was evaluated using the coefficient of determination (R^2).

Table 7: Coefficient of Determination

Endogenous Variable	***R^2***
Perceived Usefulness	0.27
Behavioral Intention	0.58
Actual Use	0.46

The model explains 58% of the variance in behavioral intention and 46% of the variance in actual system use, indicating a moderate to substantial explanatory power.

4.8 Summary of Hypothesis Testing

The empirical results support most of the hypothesized relationships in the proposed model. In particular:

- ∅ Perceived usefulness and perceived ease of use significantly influence behavioral intention.
- ∅ Social influence and trust-related factors play an important role in shaping adoption behavior.
- ∅ Facilitating conditions and ICT infrastructure are key determinants of actual system use.
- ∅ Behavioral intention strongly predicts actual use of e-health systems.

These findings confirm the relevance of integrating both traditional technology adoption constructs and contextual determinants when studying e-health implementation in fragile healthcare environments.

Discussion

This study aimed to develop and empirically validate a context-aware adoption model for e-health systems in the healthcare sector of the Democratic Republic of Congo. By integrating constructs from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) with contextual determinants relevant to fragile healthcare systems, the study provides a comprehensive understanding of the factors influencing healthcare professionals' behavioral intention and actual use of e-health technologies. The empirical findings confirm that both technological perceptions and contextual conditions play a critical role in shaping the adoption of digital health systems in resource-constrained healthcare environments.

5.1 Influence of Perceived Ease of Use and Perceived Usefulness

The results indicate that perceived ease of use significantly influences perceived usefulness, which in turn has a strong positive effect on behavioral intention to adopt e-health systems. These findings are consistent with the original propositions of the Technology Acceptance Model, which emphasizes that users are more likely to adopt a technology when they perceive it as both useful and easy to use.

In the context of healthcare environments, the perceived usefulness of e-health systems is often associated with their ability to improve clinical efficiency, facilitate patient management, and enhance access to medical information. The results of this study therefore confirm that healthcare professionals are more inclined to adopt digital health technologies when they believe that such systems can improve their professional performance.

These findings are consistent with previous studies on e-health adoption conducted in various healthcare settings, which have also highlighted the importance of perceived usefulness and perceived ease of use as key predictors of technology acceptance. However, in fragile healthcare environments such as the Democratic Republic of Congo, the perceived usefulness of e-health systems may also be influenced by broader infrastructural and organizational constraints that affect the practical benefits of digital technologies.

5.2 Role of Social Influence in E-Health Adoption

The study also found that social influence has a significant positive effect on behavioral intention, confirming the relevance of this construct within the UTAUT framework. In healthcare organizations, adoption decisions are often shaped by professional norms, leadership encouragement, and peer recommendations.
Healthcare professionals frequently operate within collaborative environments where the opinions of supervisors, colleagues, and institutional leaders can influence individual technology adoption decisions. The results suggest that institutional support and peer encouragement play an important role in promoting the use of e-health technologies within healthcare institutions.
These findings align with previous research on health information systems adoption, which has shown that social influence is particularly relevant in organizational settings where hierarchical structures and professional networks shape behavioral patterns.

5.3 Importance of Trust, Privacy, and Security

Another important finding of this study concerns the significant influence of trust, privacy, and security perceptions on behavioral intention to adopt e-health systems. In digital healthcare environments, concerns about the confidentiality and integrity of patient data can strongly affect users' willingness to adopt electronic systems.
In fragile healthcare systems, where regulatory frameworks and cybersecurity mechanisms may be less developed, healthcare professionals may exhibit greater caution when adopting digital health technologies. The results suggest that

strengthening data protection mechanisms and building trust in digital systems are essential for encouraging the adoption of e-health solutions.
These findings are consistent with previous studies that highlight the importance of trust and perceived security in the adoption of electronic health records and telemedicine platforms. The results therefore reinforce the need for robust data governance policies and secure system architectures in digital health initiatives.

5.4 Influence of Facilitating Conditions and ICT Infrastructure

The results further demonstrate that facilitating conditions and ICT infrastructure significantly influence the actual use of e-health systems. This finding supports the UTAUT proposition that the availability of technical resources and organizational support is a key determinant of technology utilization.
In the context of the Democratic Republic of Congo, healthcare institutions often face infrastructural challenges, including limited internet connectivity, unreliable electricity supply, and insufficient ICT equipment. These constraints may limit the effective implementation of digital health technologies even when users express positive attitudes toward their adoption.
The significant effect of ICT infrastructure observed in this study highlights the importance of investing in digital infrastructure to support the successful deployment of e-health systems. Without adequate technological resources, healthcare professionals may be unable to fully integrate digital systems into their daily clinical practices.

5.5 Behavioral Intention as a Predictor of Actual Use

Consistent with previous technology adoption research, the findings confirm that behavioral intention strongly predicts the actual use of e-health systems. Healthcare professionals who express a strong intention to use digital health technologies are more likely to integrate these systems into their routine professional activities.
This result reinforces the central role of behavioral intention in technology adoption models and confirms that fostering positive attitudes toward e-health systems is essential for ensuring their effective implementation.
However, the findings also suggest that behavioral intention alone is insufficient to guarantee actual system use if infrastructural and organizational conditions are not supportive. Therefore, successful e-health implementation requires both user acceptance and enabling environmental conditions.

5.6 Implications for E-Health Adoption in Fragile Health Systems

Overall, the results highlight the importance of adopting a context-aware approach to e-health implementation in fragile healthcare environments. While traditional technology adoption models such as TAM and UTAUT provide valuable insights into individual perceptions and behavioral intentions, they may not fully capture the complex contextual realities of developing healthcare systems.
By integrating contextual determinants such as ICT infrastructure, trust, privacy, and policy support, the proposed model provides a more comprehensive understanding of the factors that influence e-health adoption in the Democratic Republic of Congo.

The findings therefore contribute to the growing body of literature that emphasizes the importance of adapting technology adoption frameworks to specific socio-technical contexts, particularly in developing countries where infrastructural and institutional conditions significantly shape digital transformation processes.

Theoretical and Practical Implications

6.1 Theoretical Implications

This study makes several important theoretical contributions to the literature on digital health adoption, particularly in the context of fragile healthcare systems and developing countries.

First, the study contributes to the extension of technology adoption theories by integrating constructs from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) with contextual determinants that are particularly relevant in resource-constrained healthcare environments. While TAM and UTAUT have been widely applied in information systems research, their application in fragile health sectors often requires adaptation to account for infrastructural, institutional, and regulatory challenges. By incorporating variables such as ICT infrastructure, trust, privacy and security, and policy environment, the proposed model provides a more context-sensitive framework for analyzing e-health adoption.

Second, this research contributes to the growing body of knowledge on e-health adoption in developing countries. Much of the existing literature on digital health technologies has focused on high-income countries with relatively advanced technological infrastructures. In contrast, healthcare systems in many developing countries face significant challenges related to limited digital infrastructure, insufficient technical support, and weak regulatory frameworks. The findings of this study therefore provide empirical evidence on how contextual conditions shape the adoption of digital health technologies in fragile healthcare environments.

Third, the study contributes to the literature on socio-technical perspectives of health information systems by demonstrating that successful adoption of e-health technologies is not solely determined by users' perceptions of system usefulness or ease of use. Instead, adoption outcomes are shaped by a complex interaction between technological characteristics, individual perceptions, organizational support mechanisms, and broader institutional environments.

Finally, this research contributes to the emerging discussion on context-aware digital transformation models in healthcare. The results highlight the importance of designing technology adoption models that account for the realities of healthcare systems operating in constrained environments. This perspective reinforces the need for adaptive theoretical frameworks capable of capturing both human and infrastructural dimensions of digital health innovation.

6.2 Practical Implications

Beyond its theoretical contributions, this study also provides important practical insights for policymakers, healthcare managers, and technology developers involved in the implementation of e-health systems in developing countries. For policymakers, the findings emphasize the importance of establishing a supportive policy and regulatory environment for digital health initiatives. Effective e-health implementation requires clear national strategies, regulatory frameworks for data protection, and standards that ensure interoperability between different health information systems. Policymakers should therefore prioritize the development of digital health governance structures that promote innovation while ensuring patient data privacy and security.

For healthcare institutions, the results highlight the critical role of facilitating conditions and organizational support in encouraging the use of e-health technologies. Healthcare organizations should invest in capacity building programs, digital literacy training for healthcare professionals, and technical support systems that help users integrate digital tools into their daily clinical practices. Institutional leadership also plays an important role in fostering a culture that encourages digital innovation and technology acceptance among healthcare staff.

For system designers and technology developers, the findings underline the importance of designing user-centered e-health systems that are easy to use, reliable, and aligned with the practical needs of healthcare professionals. Systems that are perceived as complex or difficult to use may face resistance from healthcare workers who already operate under significant workload pressures. Developers should therefore prioritize usability, system reliability, and integration with existing healthcare workflows when designing digital health platforms.

Additionally, the results highlight the importance of strengthening ICT infrastructure in healthcare institutions. Reliable internet connectivity, stable electricity supply, and adequate computing equipment are essential prerequisites for the effective deployment of digital health technologies. Without these foundational elements, even well-designed e-health systems may fail to achieve their intended impact.

Finally, the findings emphasize the importance of building trust in digital health technologies. Healthcare professionals must be confident that patient data are protected and that digital systems operate securely. Implementing robust cybersecurity measures and transparent data governance practices can therefore play a key role in promoting the acceptance and sustained use of e-health platforms.

6.3 Implications for Digital Health Implementation in Fragile Contexts

The results of this study suggest that successful e-health implementation in fragile healthcare systems requires a holistic and context-aware approach. Rather than focusing exclusively on technological solutions, digital health strategies should address the broader socio-technical ecosystem in which these technologies

operate.

This includes strengthening digital infrastructure, developing supportive policy frameworks, enhancing digital skills among healthcare professionals, and ensuring that system architectures are designed with interoperability, security, and scalability in mind. By adopting such an integrated approach, stakeholders can increase the likelihood that e-health initiatives will achieve sustainable and meaningful improvements in healthcare delivery (Kalema, Businge, Julius, & Vincent, 2026).

Conclusion

This study investigated the factors influencing the adoption and use of e-health systems in the healthcare sector of the Democratic Republic of Congo by developing and empirically validating a context-aware adoption model. By integrating key constructs from established technology acceptance frameworks with contextual determinants relevant to fragile healthcare environments, the research provides a comprehensive understanding of the drivers and barriers affecting digital health implementation.

The results demonstrate that the adoption of e-health technologies in healthcare institutions is influenced by a combination of technological perceptions, social dynamics, and contextual conditions. In particular, perceived usefulness, perceived ease of use, social influence, and trust-related factors play a significant role in shaping healthcare professionals' behavioral intention to adopt digital health systems. At the same time, infrastructural conditions and organizational support mechanisms were found to strongly influence the actual use of these systems within healthcare institutions.

These findings confirm that while traditional technology acceptance models remain valuable for understanding individual perceptions toward digital technologies, they must be complemented by contextual factors when applied to fragile healthcare systems. In developing countries, the availability of ICT infrastructure, institutional support, regulatory frameworks, and data security mechanisms are critical elements that determine whether digital health initiatives can be effectively implemented.

From a theoretical perspective, the study contributes to the literature by proposing a context-aware model that extends traditional technology adoption frameworks to better reflect the realities of healthcare systems in developing regions. By incorporating infrastructural and institutional determinants alongside individual-level perceptions, the proposed framework provides a more holistic understanding of e-health adoption dynamics in resource-constrained environments.

From a practical perspective, the findings highlight the need for coordinated efforts among policymakers, healthcare institutions, and technology developers to ensure the successful implementation of e-health systems. Strengthening digital infrastructure, improving healthcare professionals' digital competencies, establishing clear regulatory frameworks, and ensuring data privacy and security

are essential steps for promoting sustainable digital transformation in the healthcare sector.

Furthermore, the study underscores the importance of designing e-health architectures that are adaptable to local healthcare contexts while maintaining interoperability and scalability. Such architectures can facilitate the integration of various health information systems and support more efficient healthcare service delivery.

Overall, this research highlights the strategic importance of adopting context-sensitive approaches to digital health implementation in developing countries. By addressing both technological and environmental factors, stakeholders can increase the likelihood that e-health initiatives will improve healthcare accessibility, efficiency, and quality of care.

Future research could further explore the long-term impacts of e-health adoption on healthcare performance and patient outcomes, as well as investigate additional contextual variables that may influence digital health implementation in other developing regions. Such efforts would contribute to a deeper understanding of how digital technologies can support resilient and inclusive healthcare systems worldwide.

Conflicts of interest

The authors declare no conflicts of interest.

References

A. Narh, James, T., & Patricia, A. (2012). A revised UTAUT model to investigate E-health acceptance of health professionals in Africa. *Journal of Emerging Trends in Computing and Information Sciences*. doi:doi=aae7ae74d445b32fd5a61c6b37bcc7a5aa3f436a

A., K., M. Shafiq, & P. Kakria. (2020). Investigating acceptance of telemedicine services through an extended technology acceptance model (TAM). *Technology in Society*, 60. doi:10.1016/j.techsoc.2019.101212

Aamir, J., Ali, M., Boulos, M., Anjum, N., & Ishaq, M. (2017). Enablers and inhibitors: A review of the situation regarding mHealth adoption in low- and middle-income countries. *Health Policy and Technology, 7*(1), 88–97. doi:10.1016/J.HLPT.2017.11.005

Ajzen, I. a. (1980). Understanding attitudes and predicting social behavior Prentice Hall. Retrieved 10 13, 2024, from http://search.epnet.com/login.aspx?direct=true&db=apd&authdb=epref&an=AUP SB.AJZEN.PRENTICEHALL.ALHJ

Ajzen, I., & M. Fishbein. (1980:). *Understanding attitudes and predicting social behavio.* Prentice Hall.

Alhashmi, S., Salloum, S., & Mhamdi, C. (2019). Implementing Artificial Intelligence in the United Arab Emirates Healthcare Sector: An Extended Technology Acceptance Model. *Int. J. Inf. Technol. Lang, 3*, 27–42.

Alsswey, A., & Al-Samarraie, H. (2019). Elderly users' acceptance of mHealth user interface (UI) design-based culture: the moderator role of age. *J Multimodal User Interfaces*(doi: 10.1007/s12193-019-00307-w Google Scholar), 49–59.

An, X., Chai, C., Li, Y., Zhou, Y., Shen, X., Zheng, C., & Chen, M. (2024). Modeling English teachers' behavioral intention to use artificial intelligence in middle schools. *Education and Information Technologies, 28*(5), 5187-5208. doi:doi.org/10.1007/s10639-022-11286-z

Anugraheni, T. D., Izzah, L., & Hadi, M. S. (2023). Increasing the students' speaking ability through role-playing with Slovin's Formula Sample Size. *Jurnal Studi Guru Dan Pembelajaran, 6*(3), 262-272. doi:doi.org/10.30605/jsgp.6.3.2023.2825

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the academy of marketing science, 16*(1), 74-94.

Barbarella, F., Melchiorre, M., Quattrini, S., Papa, R., & Lamura, G. (2022). How Can eHealth Improve Care for People With Multimorbidity in Europe? *European Observatory on Health Systems and Policies*. Retrieved from http://www.icare4eu.org/pdf/PB_25.pdf

Barlow, J., Bayer, S., & Curry, R. (2006). Implementing complex innovations in fluid multi-stakeholder environments: Experiences of 'telecare',. *Technovation, 26*(3), 396-406. doi:https://doi.org/10.1016/j.technovation.2005.06.010

Barlow, J., Bayer, S., & Curry, R. (2006). Implementing complex innovations in fluid multi-stakeholder environments: Experiences of telecare. *Technovation, 26*(3), 396-406. doi:https://doi.org/10.1016/j.technovation.2005.06.010

BOORE, C. (2018). A FRAMEWORK FOR E-HEALTH IMPLEMENTATION IN THE HEALTH CARE SECTOR IN KENYA: A GROUNDED THEORY APPROACH. NAIROBI: UNIVERSITY OF NAIROBI.

Chan, M., Khoo, Y., Stona, A., Joarder, T., de Alwis, R., Vogel, S., & Tan-Koi, W. (2025). Regulatory factors affecting sustainable vaccine manufacturing in Asia and the Pacific: Findings from a scoping review and semi-structured interviews. *Vaccine*. doi:doi.org/10.1016/j.vaccine.2025.127607

Connelly, L. M. (2022). Measurement instrument validity. *Medsurg Nursing, 31*(1), 64-63.

Danso, K. O., Asagba, P. O., Yarhere, I. E., Adumattah, P., & Amoaful, S. (2024). Implementing and adopting EHR systems in developing countries. *Ghana Journal of Nursing and Midwifery, 1*(4), 30-62.

Dhindsa, B., Narang, M., & Choudhary, K. (2013). Benefits and challenges of e-governance portal. *International Journal of Soft Computing and Engineering, 3*(5), 121-13.

Djamba, K. J., & Irene, B. N. (2024). Integration D'une Application Mobile Au Systeme De Regulation Du Niveau D'eau D'un Reservoi. *British Journal of Multidisciplinary and Advanced Studies, 5*(1), 8-22. doi: https://doi.org/10.37745/bjmas.2022.0388

Djamba, K. J., Havyarimana, V., Mbabazi, B. P., & Niyongabo, J. (2025). Understanding E-Health Implementation in the Democratic Republic of the Congo: A Systematic Literature Review. *Nigerian Journal of Technological Development, 22*(5), 169-184. doi:doi.org/10.63746/njtd.v22i5.3269

Djamba, K. J., Havyarimana, V., Mbambazi, B. P., & & Niyongabo, J. (2025). E-Health Implementation in the Democratic Republic of the Congo: Current Position. *International Journal of Health Sciences, 9*, 210-222.

Djamba, K. J., Havyarimana, V., Mbambazi, B. P., & Niyongabo, J. (2025). E-Health Implementation in the Democratic Republic of the Congo: Current Position. *International Journal of Health Sciences, 9*(1), 210-222. doi:https://doi.org/10.53730/ijhs.v9n1.15543

Djamba, K. J., Prince, M. S., Havyarimana, V., Josue, L. K., Blaise, C. M., & Jonathan, K. D. (2025). Machine-Learning Prognostic Models From The 2018–2020 Ebola Outbreak in Democratic Republic of Congo. *Scientific Journal of Engineering, and Technology, 2*(1), 101-111. doi:https://doi.org/10.69739/sjet.v2i1.470

Ekaimi, S., Utomo, P., Gunawan, D., Jimmy, S., Christian, & M. (2024). Examining the Factors Influencing Teleconsultation Adoption During the Pandemic Using the TAM Model. *Glob. Bus. Financ. Rev, 29*, 149–160. doi:10.17549/gbfr.2024.29.3.149

Etty, N., Karen, S., & Monika, G. (2020). Implementation of eHealth Technology in Community Health Care: the complexity of stakeholder involvement. *BMC Health Services Research*. doi:https://doi.org/10.1186/s12913-020-05287-2

Eysenbach, G. (2023). Editorial: Poverty, Human Development, and the Role of e-Health. *Journal of Medical Internet Research, 4*, 34.

F. Davis. (1989). Perceived Usefulness, Perceived Ease of Use and User Acceptance of Information Technology. *MIS Quarterly, 13*(3), 319-340.

F. Davis. (1989). *Perceived usefulness, perceived ease of use, and user acceptance of information technology*. Minnesota: Management Information Systems Research Center, University of Minnesota.

F. Davis, P. Bagozzi, & P. Warshaw. (1989). User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Manag. Sci, 35*, 982–1003. doi:10.1287/mnsc.35.8.982

FakhrHosseini, S., Chan, K., Lee, C., Jeon, M., Son, H., Rudnik, J., & Coughlin, J. (2024). User adoption of intelligent environments: A review of technology adoption models, challenges, and prospects. *International Journal of Human–Computer Interaction, 40*(4), 986-998.

Feng, K., & Haridas, D. (2025). A unified model integrating UTAUT-Behavioural intension and Object-Oriented approaches for sustainable adoption of Cloud-Based collaborative platforms in higher education. *Sci Rep*, 24767. doi:doi.org/10.1038/s41598-025-08446-9

Fettermann, D., & Calegari, L. (2024). E-health technology acceptance: a meta-analysis. *Ciência Da Informação, 52*(2). doi:doi.org/10.18225/ci.inf.v52i2.7089

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research, 18*(1), 39-50.

Glanz, K., & Bishop, D. (2018). The role of behavioral science theory in development and implementation of public health interventions. *Annual Review of Public Health, 36*, 399-418.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European business review, 31*(1), 2-24.

HWANG, H. J. (2023). The importance of anonymity and confidentiality for conducting survey research. *Journal of Research and Publication Ethics, 4*(1), 1-7.

James, A., & Patricia, W. (2017). A revised UTAUT model to investigate E-health. *Journal of Emerging Trends in Computing and Information Sciences, 3*(10), 3.

K. Josue, Vincent. Havyarimana, Businge. Pheliix, & Julius. Niyongabo. (2026). A Context-Aware Information Systems Architecture for Sustainable E-Health

Implementation in the Democratic Republic of Congo. *J Health Inform Afr, 13*(1), 78–95. doi:10.12856/JHIA-2026-v13-i1-669.

Kalema, J., Businge, M., Julius, N., & Vincent, H. (2026). A Service-Oriented, API-Driven Framework for Interoperability of Health Information Systems in the Democratic Republic of Congo. *INTERNATIONAL JOURNAL OF ENGINEERING RESEARCH & TECHNOLOGY (IJERT), 15*(03). doi:doi.org/10.5281/zenodo.19468708

Karamagi, H. C., Muneene, D., Droti, B., Jepchumba, V., Okeibunor, J. C., Nabyonga, J., & Kipruto, H. (2022). eHealth or e-Chaos: The use of Digital Health Interventions for Health Systems Strengthening in sub-Saharan Africa over the last 10 years: A scoping review. *Journal of global health, 12*.

Kovačić M., M. M. (2022). E-health application, implementation and challenges: a literature review. *Business Systems Research: International journal of the Society for Advancing Innovation and Research in Economy, 1*(1-18), 13.

Krisdina, S., Nurhayati, O. D., & Nugraheni, D. M. (2022). Hybrid Model Based on Technology Acceptance Model (TAM) & Information System Success Model (ISSM) in Analyzing the Use of E-Health. *E3S Web of Conferences*. doi:10.1051/e3sconf/202235905003

Luo, Z. (2023). Determinants of the perceived usefulness (PU) in the context of using gamification for classroom-based ESL teaching: A scale development study. *Education and Information Technologies, 28*(4), 4741-4768.

Maita, K. C., Maniaci, M. J., Haider, C. R., Avila, F. R., Torres-Guzman, R. A., Borna, S., & Forte, A. J. (2024). The impact of digital health solutions on bridging the health care gap in rural areas: a scoping review. *The Permanente Journal, 28*(3), 130.

Mbanaso, U. M., Abrahams, L., & Okafor, K. C. (2023). Research philosophy, design and methodology. In Research Techniques for Computer Science, Information Systems and Cybersecurity. *Cham: Springer Nature Switzerland.*, 81-113. doi:doi.org/10.1007/978-3-031-30031-8_6

Nguyen, H., Tapanainen, T., Zaza, S., & Huvila, I. (2024). Antecedents of Perceived Usefulness (PU) and Perceived Ease-of-Use (PEOU) in the Heuristic-Systematic Model: The Context of Online Diabetes Risk Test. *Journal of Information Technology Applications and Management, 31*(5), 17-39. doi:org/10.21219/jitam.2024.31.5.017

Nii Laryeafio, M., & Ogbewe, O. C. (2023). Ethical consideration dilemma: systematic review of ethics in qualitative data collection through interviews. *Journal of Ethics in Entrepreneurship and Technology, 3*(2), 94-110. doi:10.1108/JEET-09-2022-0014

Ráti, J., & Ildikó, K. (2023). Factors influencing the adoption of e-health services by the patients. *Corvinus Research,University of Budapest*, 2.

Ráti, J., & Ildikó, K. (2023). Factors influencing the adoption of e-health services by the patients. *Corvinus Doctoral Schools*, 1.

Raynaud, J. (2022). L'e-santé en France: déclinaisons et implications territoriales. E-health in France: territorial variations and implications. *Netcom. Réseaux, communication et territoires,*, (36-3/4).

S. Ekaimi, P. Utomo, D. Gunawan, S. Jimmy, & M. Christian. (2024). Examining the Factors Influencing Teleconsultation Adoption During the Pandemic Using the TAM Model. *Glob. Bus. Financ. Rev, 29*, 149–160. doi:10.17549/gbfr.2024.29.3.149

Taylor S. & Todd, P. A. (1995). Assessing IT Usage: The role of prior experience. MIS Quarterly. *19*. Retrieved 10 13, 2024, from http://search.epnet.com/login.aspx?direct=true&db=aph&authdb=epref&an=MQ. AI.EFA.TAYLOR.AIURPE

Ursavaş, Ö. F. (2022). Unified theory of acceptance and use of technology model (UTAUT). In Conducting technology acceptance research in education: Theory, models, implementation, and analysis. *Cham: Springer International Publishing*, 111-133.

Velmurugan, S., Prakash, M., Neelakandan, S., & Radhakrishnan, A. (2024). Provably secure data selective sharing scheme with cloud-based decentralized trust management systems. *Journal of Cloud Computing, 13*(1), 86. doi:doi.org/10.1186/s13677-024-00634-8

Venkatesh, V., Morris, M., Davis, B., & Maheshwari, F. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 3*(27 [DOI:10.2307/30036540]]), 425-478.

Vest, J. (2010). More than just a question of technology: factors related to hospitals' adoption and implementation of health information exchange. *Int J Med Inform., 79*(12), 797-806. doi: DOI: 10.1016/j.ijmedinf.2010.09.003

Walle, A. D., Demsash, A. W., Adem, J. B., Wubante, S. M., Shibabaw, A. A., Mamo, D. N., & Ferede, T. A. (2023). Exploring facilitators and barriers of the sustainable acceptance of e-health system solutions in Ethiopia: a systematic review. *PLoS One, 18*(8).

WHO. (2023). World Health Statistics 2023: Monitoring health for the SDGs, sustainable development goals. Geneva.

Zin, K., Kim, S., Kim, H., & I.F., F. (2023). A Study on Technology Acceptance of Digital Healthcare among Older Korean Adults Using Extended Tam (Extended Technology Acceptance Model) Adm. *Sci, 13*, 42. doi:10.3390/admsci13020042

Zoccarato, F., Manzoni, M., Minotti, D., Lettieri, E., & Boaretto, A. (2024). Unveiling the interplay between rational, psychological and functional factors in continuous glucose monitoring early adoption: Novel evidence from the Dexcom ONE case in Italy. *BMC Health Serv. Res*(24), 747. doi:10.1186/s12913-024-11195-6